Management System for the Fattening Process of Bovines in Rotational Grazing using Diagnosis and Recommendation System

Rodrigo García
GIDITIC, Universidad EAFIT
Faculty of Engineering, Universidad de Córdoba,
Faculty of Engineering, Universidad del Sinú,
Monteria, Colombia,
rjgarciah@eafit.edu.co

and

Charles Benitez
CEMISID, Universidad de Los Andes,
Merida, Venezuela,
charlesjbenitez1993@gmail.com

and

Jose Aguilar
GIDITIC, Universidad EAFIT
IMDEA Networks Institute, Leganes
CEMISID, Universidad de Los Andes,
Merida, Venezuela,
aguilar@ula.ve

Abstract

Cattle breeding has been one of the most important industrial sectors in the world since it is related to food security and the survival of the human race. Management of the cattle fattening process is a fundamental procedure for cattle breeders because it allows them to make strategic decisions, such as timely treatment in case of any abnormality (e.g., weight gain in herds, in their paddocks). This article aims to present a management system for the cattle fattening process under a rotational grazing scheme, considering the health status of the animal and the pasture, which should diagnose weight loss or gain in bovines and recommend actions when is required. The diagnostic process is based on a fuzzy system that defines rules that characterize the diagnostic process to determine the current situation given an input. Furthermore, the fuzzy classifier optimizes its rules by means of genetic algorithms by modifying its membership functions, providing a more accurate system for diagnosis. On the other hand, the recommendation system is based on a classification model of pasture crops, in which the best pasture is recommended given the soil variables. We tested our proposal with experimental cases, with promising results. For the fuzzy classifier, the accuracy metrics are very good, with values of accuracy close to 100% and of *Area Under the Curve* close to 1. For the classification model were used several machine learning techniques, resulting in the best classifier the random forest technique, with an accuracy of 98.61%.

Keywords: Precision Livestock Farming, Rotational Grazing, Diagnostic System, Recommendation System

1 Introduction

The livestock activity in the nations located in the tropics is becoming more and more demanding due to demographic growth, so this activity must constantly assume dynamics of transformation and adaptation [1]. On the other hand, the intertropical climatic seasons are characterized by winter and summer, which condition the livestock activity in terms of animal feeding, so it is necessary to improve the feeding processes considering these aspects so that this activity generates greater volumes of profit [2]. At the same time, the livestock industry presents a series of difficulties to detect failures in its production systems, which directly affects the ideal growth of livestock and the optimum production of paddocks [3]. The problem lies in the inability to make decisions in real time, using data, of what may be happening in the cattle fattening process. Therefore, it is necessary to develop a management system for the cattle fattening process, with the objective of helping farmers make decisions to increase production efficiency.

1.1 Related Works

Some works related to our proposal are the following. Palomino and Loza [4] designed a rotational grazing system for a high Andean dairy herd. The purpose of this project was to improve traditional grazing systems for dual-purpose high Andean dairy cattle. SAS Planet software was used for the design, and plans of the farm and areas for agriculture and housing purposes were plotted to determine the ideal number of paddocks and the optimal stocking rate.

Plaza et al. [5] proposed a fuzzy system to recommend fertilization plans in soils and grasslands. Influential variables are characterized and fuzzy sets and membership functions based on ideal productions are designed. Also, Castelao et al. [6] applied fuzzy logic to make decisions based on data related to agricultural and livestock productivity in rural settlements. The production of corn, beans, cassava, beef, pork, and poultry in 26 settlements was analyzed. In addition, Pena et al. [7] proposed a methodology based on fuzzy logic to improve farmers' decision-making when selecting crop species. This approach offers advantages over the current trial-and-error approach by allowing the systematization of expert knowledge on pastures, soils and climate for more objective decisions.

Several authors [8, 9] outline the essential aspects for developing low-carbon livestock farming. They considered a set of effects related to climate change, and their impact on the soil-plant-animal relationship. They propose an intensive grazing system that guarantees low-emission livestock farming, which represents an option in the face of climate change. Garcia et al [10]. propose an approach to detect anomalies in the cattle fattening process. This approach uses the actual historical record of animal weight to identify whether animals have gained the appropriate weight over time. They compare several machine learning techniques (Decision Tree, Gradient Boosting, regression based on K-Nearest Neighbors and Random Forest) in the task of anomalous weight detection, using Mean Absolute Error as quality metrics.

On the other hand, regarding fuzzy classifier systems, Ramirez et al [11]. designed a fuzzy classifier system for the establishment of the functional states of a medical production system. For the design and tuning of the fuzzy classifier, the process data history was used to identify all functional states useful for process monitoring. The establishment of functional states from the fuzzy classification allows the programming of corrective actions in the process from the diagnosis performed. Finally, in [12] they applied fuzzy logic and genetic algorithms for the determination of treatments in malignant neoplastic diseases. The paper proposes an optimized fuzzy classifier using a hybrid genetic algorithm with a fuzzy clustering technique. They implement a prototype and evaluate it on synthetic treatment data against malignant neoplastic diseases. Finally, previous work has determined that machine learning is essential to provide self-management capability in a beef production farm [13].

1.2 Contribution

This work aims to propose a management system for the cattle fattening process, which contains a system to diagnose the individual fattening progress, and the causes of cattle weight loss or gain, in rotational grazing, but in addition, it has a system to recommend the best pasture given the soil variables for each paddock of the farm. *The diagnostic system* is based on fuzzy theory, and uses rules to analyze the current cattle weight situation. In addition, the system optimizes the rules to fit the actual data of the cattle under supervision. On the other hand, *the recommendation system* is based on a classifier model built with machine learning techniques. Particularly, 6 algorithms were used: nearest neighbors, decision tree, gradient boosting, logistic regression, support vector machines and random forest, resulting the last one with higher accuracy.

The organization of this work is as follows. Section 2 presents the theoretical framework used in this work. Section 3 shows the design of our cattle fattening process management system. Then, Section 4 describes the experiments conducted with the system to evaluate its quality. Next, Section 5 compares this work with previous work. Finally, Section 5 presents the conclusions.

2 Theoretical framework

2.1 Fuzzy Classifier System

In general, fuzzy systems have proven to be very useful for representing the behavior or dynamics of systems by means of fuzzy rules. Traditionally, these systems are based on information provided by experts; however, in complex systems, the rules thus constructed did not allow an accurate simulation of the system [14]. The search for fuzzy systems that adapt to the dynamics of complex systems has led to the development of research on techniques for extracting fuzzy rules from input and output data [15–19]. Fuzzy classification algorithms represent one of the techniques for the development of adaptive fuzzy systems [20, 21].

A Fuzzy Classifier System is composed of two major components. A *rules subsystem* that allows classifying the input information. This subsystem defines the rules of type *If-Then* using fuzzy variables, and uses a fuzzy reasoner to infer a conclusion. The second component of a fuzzy classifier system is the *adaptive subsystem*. Traditionally, this subsystem is based on genetic algorithms (GA), which are inspired by biological evolution as a strategy for solving optimization problems [22]. In particular, the fuzzy classifier uses it to optimize the rules, and thus, its performance.

2.2 Recommendation System

Our recommendation system is based on a classification model, which is previously trained with the information to be recommended, such that for a given input, it knows which recommendation to give. The classification model is built using supervised machine learning techniques. Specifically, these models are built from a training process using a set of labeled data. Then, that trained model is used to predict/determine the class to which a new unknown input belongs. Thus, once trained, it is used to assign a label or class to a new data entry [23].

Different types of machine learning algorithms (based on search trees, etc.) have been used to determine which of them behaves best in our context:

- Near neighbors: This algorithm is based on the idea that an entry is more similar to entries that are close to it in the feature space. [24].
- Decision Tree: This algorithm builds a tree that represents the decisions that must be made to arrive at a classification [25].
- Random Forest: This algorithm combines several decision trees to improve overall accuracy and reduce model variability [26].
- Gradient Boosting combines simple decision trees in iterations to create a robust and accurate model, correcting previous errors [27].
- Logistic Regression is a method for predicting class probabilities in classification problems using a logistic function [28].
- Support Vector Machines are algorithms that find optimal hyperplanes to separate classes in classification and regression problems [29].

2.3 Precision livestock farming

Precision livestock farming is one of the sectors that has incorporated the most innovations in recent years, thanks to the development of technologies aimed at improving the efficiency of livestock farms and the quality of animal products. These technologies make it possible to optimize resources, increase yields, control environmental impact and improve animal welfare. This requires monitoring animal health and production, measuring physiological and morphological biometric indicators, among other things [30].

In the case of diagnostic processes, the use of precision livestock farming allows the development of a friendly, non-intrusive monitoring technology, allowing interaction between experts and producers. In particular, diagnostic systems in precision livestock farming seek to reduce losses and improve productivity in the long term, through dynamic follow-up and monitoring of livestock. For example, a diagnostic system could evaluate quantitative information to characterize animals quickly and adequately, by studying individual and/or batches of animals. The system would interpret animal health and determine paddock performance to identify patterns in the production process, and from there, be able to diagnose possible causes of low or high fattening of cattle [10].

3 Design of the Cattle Fattening Process Management System

This section will discuss the design and operation of the fuzzy classifier-based diagnostic system and the classification model-based recommender system. A knowledge engineering process was carried out to extract all the knowledge from the experts, which was the basis for designing the system components. Consultations were carried out with groups of experts made up of farmers, veterinarians, zootechnicians and agronomists, who specified all the components of the system.

3.1 Diagnostic System Specification

The architecture of the diagnostic system is based on a fuzzy classifier system, which can be seen in Figure 1. In this Figure, 2 blocks (components) are observed, the first block, called *fuzzy rule design and optimization system*, and the second one is called the *fuzzy system*. In Figures 2 and 3, respectively, both components are detailed.

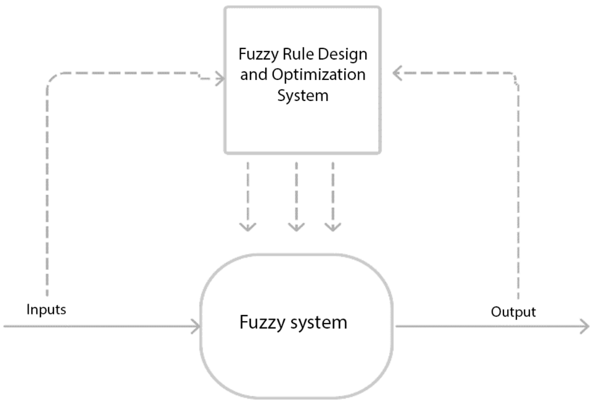

Figure 1: Fuzzy classifier architecture.

Figure 2 shows the first component, defined by the fuzzy rule design system and optimization system. The rules are designed and created using a fuzzy clustering algorithm (fuzzy rule design system). The present work uses the *fuzzy-c-means* (FCM) algorithm, which allows fuzzy data clustering (each cluster determines a fuzzy set for the linguistic/fuzzy variable of interest) [4, 31–34]. On the other hand, a GA is used for optimization (optimization system), whose task is to improve the definition of the fuzzy sets (it adapts the membership function of each fuzzy set).

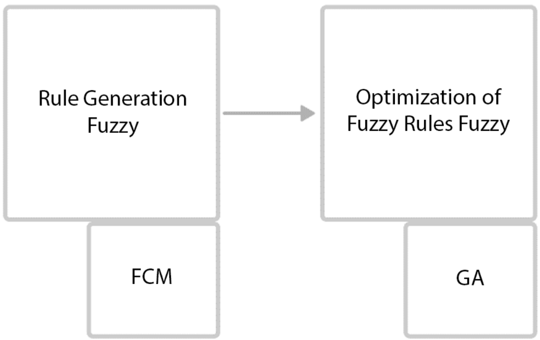

Figure 2: Fuzzy Rule Design System and Optimization System

Figure 3 shows the fuzzy system. Its components are the fuzzified input, the inference engine (fuzzy reasoner), the output generator (defuzzifier), and the knowledge base (the fuzzy rules), which is updated from time to time by the fuzzy rule optimization system shown in Figure 2.

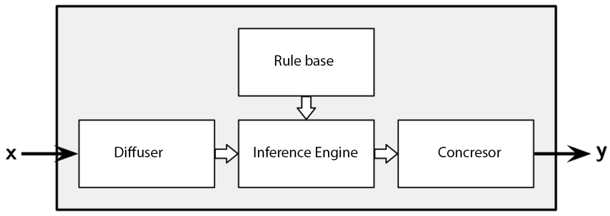

Figure 3: Fuzzy system

3.2 Specification of the fuzzy system

The fuzzy set labels, fuzzy classification system rules, among other things, were originally established with domain experts based on their experience and knowledge. As mentioned before, for this purpose, a knowledge engineering process was carried out with experts and their opinions were agreed upon. It is good to remember, that later these rules were optimized by the optimization component based on GA.

3.2.1 Fuzzy system

The engine of this system is centered on the definition of linguistic variables that make up the diagnostic model. This model is constituted by a set of fuzzy rules that use linguistic variables. Thus, the fuzzy system represents the diagnostic model proposed in this work.

The first step in designing the fuzzy system consists of creating the labels (fuzzy sets) needed for each linguistic variable. The FCM algorithm allows defining the fuzzy sets from the membership matrix that it generates for each linguistic variable [4,35]. For this purpose, FCM determines the fuzzy groups present in a linguistic variable (these will be the fuzzy sets), with the degree of membership of the values of the variable in each of them. The degrees of membership are in the range $[0, 100]$, and represent the partial membership in each fuzzy set (class) of each value of each linguistic variable. The linguistic variables, and their fuzzy sets, of our fuzzy diagnostic system, are described below.

The initial values of the trapezoids that are used in the representation of the fuzzy sets come from the expert knowledge product of the knowledge engineering process that is done with them. Remember that those values are updated by the GA-based optimization component, as these values are crucial because they affect how membership functions are modeled, and thus, how fuzzy inferences are made during classification.

The *linguistic variables* used are those linked to the fattening process. The input variables are the age, the paddock, and the differential of the final weight with the initial weight, and the output variable is the state of the animal.

- *Age:* its universe of discourse is $[0, 30]$, and represents months of life. Its fuzzy sets are $[calf, steer, adult]$. Figure 4 shows each fuzzy set.

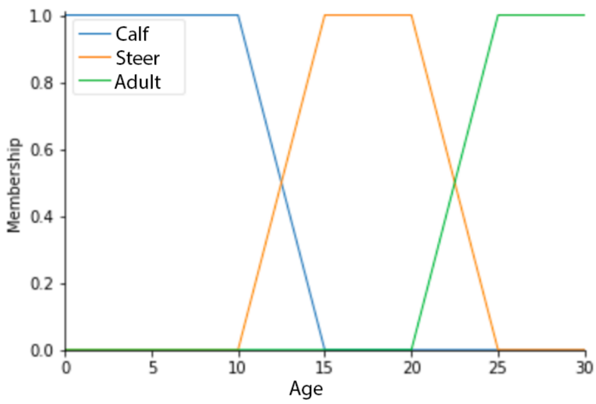

Figure 4: Variable Age

- *Differential:* its universe of discourse is $[0, 100]$, and represents the percentage of difference between the initial and current weight. Its fuzzy sets are $[low, medium, high]$. Figure 5 shows each fuzzy set.

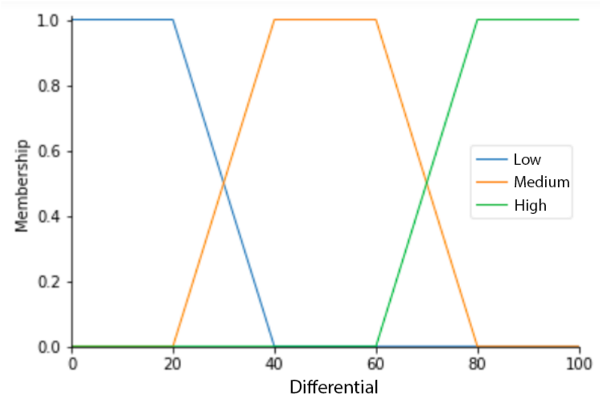

Figure 5: Variable Diferencial

- *Paddock*: its universe of discourse is $[0, 10]$, and represents the paddock yield score, characterized by forage quality and forage tolerance to the climatic situation. Its fuzzy sets are $[bad, fair, good]$. Each fuzzy set is shown in Figure 6.

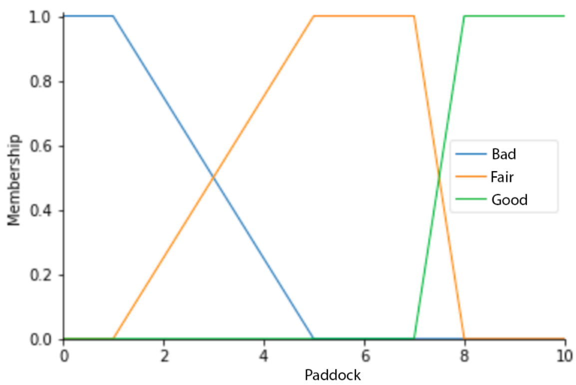

Figure 6: Variable Paddock

- *Animal Status*: its universe of discourse is $[0, 100]$, represented by a percentage to indicate how well the animal is doing. Its fuzzy sets are $[stable, sick]$. Figure 7 shows each fuzzy set.

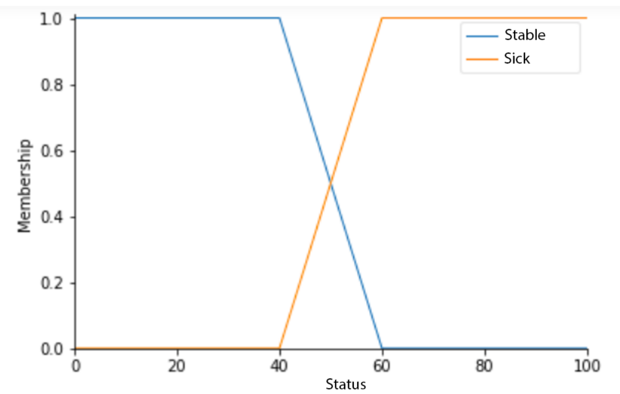

Figure 7: Variable Animal Status

3.2.2 Definition of diagnostic rules

The rules that model the system are of the form.

$$IF < \ldots > THEN < \ldots >,$$ In the following tables, we define the set of rules.

There are two different types of fuzzy rules, depending on whether information on paddock performance is available. Thus, we have a group of rules with two antecedents (see Table 1) or with three antecedents (see Table 2). Particularly, in Table 1 the two antecedents are the variables differential and age; and in Table 2 the same, but now also the paddock variable (the values of it that directly influence animal fattening, such as fair/bad). An example of a rule for the latter case is:

If the age is calf and the differential is low, and the paddock is bad, then the animal's condition is sick.

These rules will be fitted/optimized to the input dataset using GAs. Specifically, the membership functions of the fuzzy sets will be those fitted to the input data.

Table 1: Rule Base with 2 antecedents

		Diferencial		
		low	medium	high
Age	Calf	Sick	Sick/Stable	Stable
	Steer	Sick	Sick/Stable	Stable
	Adult	Sick/Stable	Sick/Stable	Stable

Table 2: Rule Base with 3 antecedents

		Diferencial				
		low	medium	high		
Age	Calf	Sick	Sick/Stable	Stable	Fair/Bad	Paddock
	Steer	Sick	Sick/Stable	Stable		
	Adult	Sick/Stable	Sick/Stable	Stable		

3.3 Characteristics of the Genetic Algorithm (GA)

3.3.1 Specification and evolution of individuals

Structure of individuals: A factor of special interest in the design of the evolutionary process to optimize the fuzzy classifier is the representation scheme used to encode each of the possible solutions. For this research, the individual is defined as follows:

Chromosome = limits of the membership function of the fuzzy sets of each linguistic variable.

In this approach, each individual represents by itself a complete solution by encoding the fuzzy sets of input and output variables. Specifically, each gene represents a vertex of the membership function of the sets of each linguistic variable, assuming a trapezoidal shape for the definition of them.

The representation of each linguistic variable would be as follows (vertices of the membership functions of their fuzzy sets):

$Age = [10, 15, 20, 25] = [e1, e2, e3, e4]$
$Differential = [20, 40, 60, 80] = [d1, d2, d3, d4]$
$Paddock = [1, 5, 7, 8] = [p1, p2, p3, p4]$
$Status = [40, 60] = [c1, c2]$

The coding of the chromosome would be the concatenation of the description of the membership function of the fuzzy sets of each variable. On the other hand, since there are rules that do not contain the fuzzy variable paddock, there are 2 cases for chromosome coding, the first one does not contain the fuzzy sets of the fuzzy variable paddock, and the second case does. Thus, in the first case, considering the order of the genes, such that the antecedents (age and differential) are placed first and then the consequent (state), the individuals are as follows (see Figure 8).

In the second case of fuzzy rules, in which paddock performance is considered in the analysis, the antecedents would be age, differential and paddock, and the consequent state (see Figure 9).

e1	e2	e3	e4	d1	d2	d3	d4	c1	c2

Figure 8: Chromosome for GA in case 1

e1	e2	e3	e4	d1	d2	d3	d4	p1	p2	p3	p4	c1	c2

Figure 9: Chromosome for GA in case 2

3.3.2 Evolution of individuals

For the optimization of fuzzy rules with GA, an initial population of individuals must be randomly generated. The objective of the GA is to modify the fuzzy sets (their membership functions) to adapt the rules to the data. The evolutionary process is as follows.

1. Individuals are selected for breeding using the following scheme:
   (a) Individuals are ordered from highest to lowest aptitude (the aptitude function is defined in the next section),
   (b) Those with aptitude lower than 0.7 are discarded.
2. Subsequently, genetic operators are used to generate new individuals. In particular, the crossover and mutation operators are used, which were implemented as follows:
   (a) Crossing: two chromosomes and the cut point are chosen randomly, to perform the cross between the two.
   (b) Mutation: a chromosome is chosen and one of its genes, chosen at random, is modified.
3. In each iteration, a number of offspring equal to the initial population size is generated, and the worst individuals in the population are replaced by the best new ones, according to the aptitude function.
4. At the end of this, if the optimum is reached or the stop condition is met, then the individual with the best value in the aptitude function is selected to update the vertices of the fuzzy sets of the fuzzy variables.

3.3.3 Aptitude Function

An aptitude function based on the calculation of the following measures was used:

Score: Measures the accuracy of an individual. In this case, as it is based on labeled data on diagnosis, the score establishes whether the consequent is true (the rule is triggered) when it should. It is calculated by the following equation:

$$Score = \frac{pv}{(pv + pf)} \tag{1}$$

Where pv is the number of true positives, and pf is the number of false positives. In particular, the score for each rule is calculated for the input dataset, and averaged.

Certainty or trigger degree of each rule: which is the activation level of a rule, calculated as the product of the membership functions of the antecedents. If the value is high, it means that the activation level of the rule is high.

Finally, the aptitude function of each individual is the average of the score of each rule multiplied by its degree of certainty. Thus, the evolutionary process, using this hybrid fitness function (score and degree of certainty), allows adjusting the fuzzy sets to fit the context data.

3.4 Specification of the Recommender System

In general, the recommendation system is based on a classifier model of livestock pasture crops. Particularly, the classification model is trained so that for a given input of soil variables, it indicates the best pasture to consider. The following steps were considered for the construction of the model:

3.4.1 Dataset acquisition

Several datasets were used from the Kaggle Crop Dataset and the Pasto certo page `www.pastocerto.com/` on pasture information. However, since information about soil physicochemical characteristics in relation to grass is very scarce, it was decided to take data from other crops similar to the different types of pastures, with the objective of having a robust dataset to train and evaluate the model. In addition to the pasture dataset, cattle were also required. Thus, the data sets used were:

- Soil nutrient content and environmental data set: This data set contains information on the main soil physicochemical variables (soil nutrients) and some environmental characteristics (maximum and minimum rainfall, maximum and minimum temperature) for 22 types of crops.
- Cattle weight gain dataset: This dataset contains information on cattle weight gain (kg) for 18 pasture types, in dry and rainy seasons.

The specific variables used from the data sets were as follows:

- Temperature: Monthly temperature (in °C).
- Moisture: relative amount of water contained in a saturated soil after 48 hours of drainage.
- Weight gain—water: gain in grams of cattle weight per day in the rainy season.
- Weight gain—dry: gain in grams of cattle weight per day in the dry season.
- Potassium: helps the plant to make more efficient use of water, it is absorbed in ionic form (K+).
- Nitrogen: It is found in two different forms: organic and chemical.
- pH: A measure of the acidity (low pH = acidic) or alkalinity (high pH = basic or alkaline) of the medium.
- Rainfall: potential capacity of rainfall to erode soils.
- Phosphorus: An essential nutrient for crops, and its lack can significantly limit crop growth and yield.

3.4.2 Data preprocessing

Since several datasets are taken for the construction of the model, the data were unified in one dataset. Thus, the new dataset contains information on the physicochemical characteristics of the soil in various crops, with the weight gains of cattle in pastures. To build the dataset, modifications were made to the soil nutrient dataset, changing the crop names to pasture types in order to combine them with the cattle weight gain dataset.

On the other hand, data preprocessing also involved substituting null values so as not to affect the overall prediction, as well as treating missing values or outliers to eliminate them.

3.4.3 Construction of the Classification Model

In this phase, supervised learning techniques were used to build the classification model. Six techniques were used to build the classifier model: K-nearest neighbors, Decision Tree Random Forest, Gradient Boosting, Logistic Regression, and Support Vector Machines.

We use cross validation in combination with techniques like GridSearchCV for the hyperparameter optimization process. GridSearchCV is a bounded search technique in which a set of possible values is specified for the model's hyperparameters. Then, all possible combinations of those hyperparameters are evaluated using cross-validation, allowing to select the combination that produces the best overall performance in terms of specific metrics, such as accuracy, F1-score, AUC, etc. GridSearchCV ensures that a range of values for each parameter has been systematically explored, helping to find the optimal combination (that maximizes model performance) [36].

Different types of techniques were used because they are widely used and known in machine learning to solve classification problems. Each of them has different strengths and weaknesses, so it is common to evaluate them beforehand to determine which one is the best fit for a specific classification task.

The results were analyzed and compared in relation to cross-validated pasture classification accuracy, as shown in Table 3. This metric is a measure commonly used in machine learning to evaluate the performance of a classification model. This metric is basic and straightforward to understand. Basically, accuracy measures the proportion of correct predictions the model makes relative to the total predictions made [37]. It is calculated by the following equation:

$$Accuracy = \frac{NumberCorrectPredictions}{TotalPredictions} \tag{2}$$

Taking as the evaluation metric the accuracy of the models, it is obtained that random forest is the best model, with a substantially high accuracy, generating an efficient classification of the categories created, with an average of 98.61% accuracy for the classes generated. The other techniques are relatively close, but the recommendation system will be defined using the classification model built with the random forest.

Table 3: Comparison between models

Algorithms	Accuracy
Nearby neighbors	98.05%
Gradient Boosting	98.55%
Logistic Regression	90.12%
Support Vector Machines	97.52%
Decision tree	96.66%
Random forest	98.61%

4 Experimentation

In this section, the behavior of our system is analyzed. For this purpose, an experimental protocol is developed describing the context where the management system is tested, and its performance is evaluated by means of quality metrics.

4.1 Experimental Context

4.1.1 Simulator

For the experiments, a livestock simulator is used (see https://github.com/devraxielh/Simulador_Ganadero), which emulates all the climatic and soil conditions of a farm, as well as the fattening behavior of the cattle. The data generated by the livestock simulator has been used in previous works [10, 38]. During its development, it was reviewed and validated by experienced farmers, agronomists and veterinarians in the field. This validation is essential to ensure that the simulation accurately and realistically reflects real world conditions on a livestock farm. In particular, the simulator generates the values of the variables that describe the land to which rotational grazing is applied, and of the cattle population being fattened. In this way, the simulator randomly generates the data that feed the fuzzy classifier system. The data of interest provided by the simulator are the following: number of animals, age of each animal, the initial weight of each animal, the evolution of the weight of each animal, number of paddocks, forage of each paddock, the climatic season of each paddock, and forage tolerance to hot climates.

4.1.2 Quality Metrics

The metrics for assessing the quality of the diagnostic and recommendation systems aim to estimate the accuracy of the models on test datasets (different from those used in the adaptive process of the rules, or training for the classification model). These are:

- Accuracy (score): It is the percentage of correct hits given by the adaptive system [39].
- Certainty degree: This is the value obtained by multiplying the membership functions of the antecedents to determine the degree of triggering of each rule and to deduce which rule is triggered more than another [40].
- ROC (Receiver Operating Characteristic) curve: This is a graph that shows the sensitivity and specificity of a model [41].
  - Sensitivity: The probability that the model predicts a positive outcome for an observation, when in fact the outcome is positive.

  - Specificity: The probability that the model predicts a negative outcome for an observation, when in fact the outcome is negative.

- Area Under the Curve (AUC): It is a numerical value given by the area of the curve generated by the ROC plot. The larger the area covered, the better the machine learning models will be at distinguishing the given classes [42]. The ideal value for AUC is 1.

4.2 Diagnostic System Test Scenarios

This section presents the case studies that will be analyzed by the diagnostic system. Each case study represents situations where climatic situations that may or may not affect the paddock are prevalent, and animal health situations are also considered. The following is a description of the case studies considered.

4.2.1 Case study 1

Objective The first case of study is the optimal case, where all animals are stable, and the paddock is suitable for use. The rules that will be activated are those of the group of 2 antecedents, since the case is ideal, then the performance of the paddock will be good and will not negatively affect the animal fattening.

System input Table 4 presents a partial view of the historical cattle fattening data (the first 4 columns). It shows the input variables (age, initial weight and final weight), but also has an identifier for each animal. On the other hand, the initial weight indicates the weight at which they enter the paddock, and the final weight represents the weight at which they leave the paddock. Considering that daily animal gain varies on average from 300 to 500 grams per day, it can be said that fattening is normal if after 30 days (time spent in each paddock) they gain approximately 8 to 15 kilos. This determines that the weight differential is within the range, and therefore it is an ideal case.

Table 4 shows in the column degree of membership of each data to the stable label group; hence, the prediction column shows the binary label 1 (as stable). These two columns represent the current prediction made by the classification system for the input data set. Table 5 shows the paddock input data. It shows the occupied paddock, the name of the forage used in the paddock and the weather situation. Table 5 shows the forage column, which represents the score the paddock has on a range of [0,10], with 10 being the highest score. This data is obtained depending on the tolerance of the forage to the climatic situation in which it is found. The status column represents the performance of the paddock according to the fuzzy interpretation to categorize paddock performance.

Table 4: Representation of livestock data and classification of animal status in experiment 1

Age (months)	Weight initial(kg)	Weight end(kg)	ID animal	Prediction	Grades membership
19	373.0205	384.4683	V1	1	0.9171
29	389.0205	400.4683	V2	1	0.9171
23	368.0205	379.4683	V3	1	0.9171
18	402.0205	413.4683	V4	1	0.9171
22	385.0205	396.4683	V5	1	0.9171
19	404.0205	415.4683	V6	1	0.9171
22	369.0205	380.4683	V7	1	0.9171
22	407.0205	418.4683	V8	1	0.9171
19	400.0205	411.4683	V9	1	0.9171
26	418.0203	427.1916	V10	1	0.9171

Table 5: Paddock performance in experiment 1

Name	Climate	Pasture	Forage	Status
Humidicola comum Tuly o Quicuio da Amazônia	Rain	6	7	Good

Analysis of results As could be seen, with the existing fuzzy rules, the fuzzy classifier system infers that all animals are stable for those input data. Once several iterations of the fuzzy system have been performed, the adaptive system of the rules is invoked (see the following figures showing the adaptation of the rules to the data).

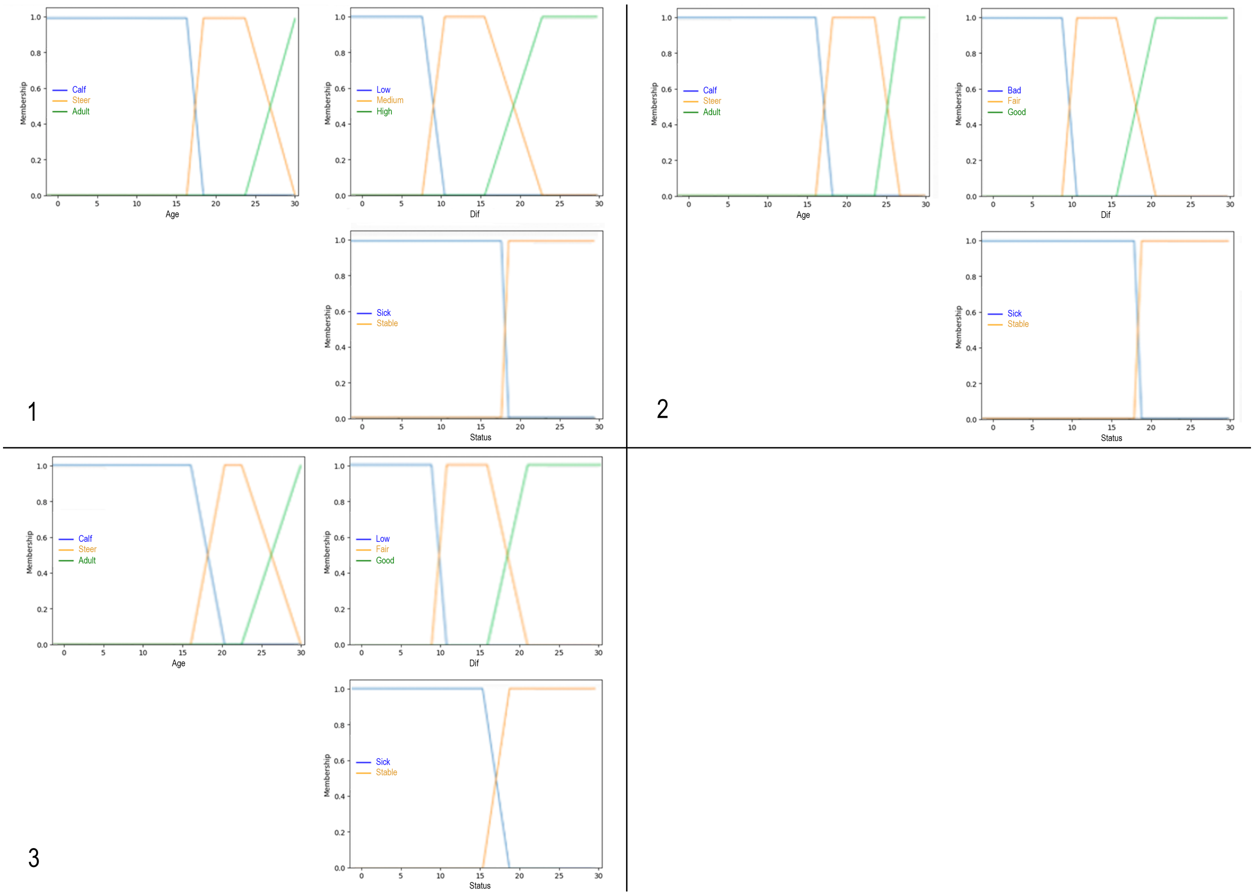

Figure 10: Adaptation of membership functions

It can be seen in Figure 10 how the fuzzy sets of each fuzzy variable are fitted using the dataset in table 4. Each represents the best individual for the first 3 iterations of the GA. For example, we see in Figure 11.1 the fuzzy sets of the antecedent and consequent of the best individual for the first iteration. The fuzzy variable of the paddock is not activated, since the performance of the paddock is good. The fuzzy rules that are activated by these settings, using the dataset from table 4, are shown in Figure 11.1. Figure 11. 2 shows the best individual of the next iteration, and its rule base, in Figure 11.2. Finally, Figure 11.3 shows the best individual when the GA is stopped, either because the stopping condition is satisfied or because it found the optimum. The final rule base shown in Figure 11.3 are the necessary system rules for the dataset in Table 4. The individual in Figure 11.3 represents the potential solution, and by comparing the final activated rules (Figure 11.3) with the dataset shown in the 4 box labeling all stable animals, we see that consistently the activated rules have in the consequent only the label stable.

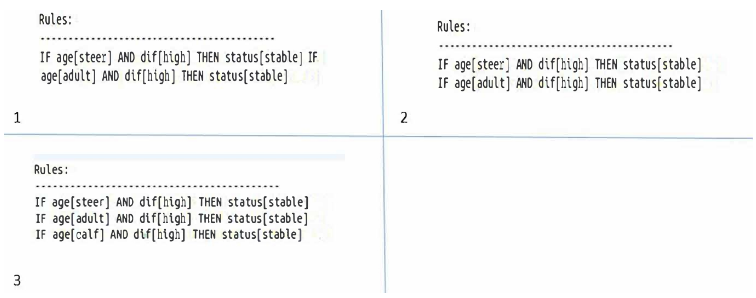

Figure 11: Evolution of the activated rules in case 1

Table 6: Case 1 metrics.

Metrics	Values
Accuracy	100%
Certainty of rules	R1:0.85, R2: 0.88,R3: 0.89
AUC	1

Finally, with the final fuzzy rules (see Figure 11) we proceed to diagnose using the test dataset. With the result of the inference process for each individual, we proceed to calculate the averages of the system quality metrics (see Table 6 and Figure 12).

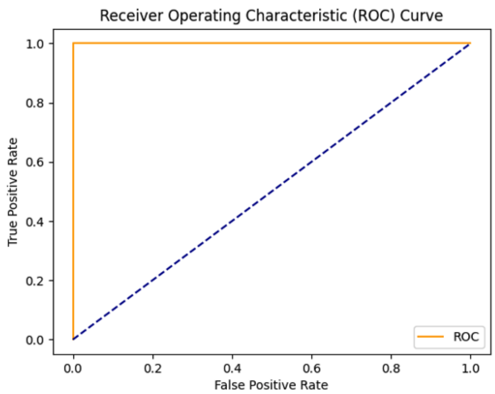

Figure 12: ROC curve case 1

The ROC curve determines the performance of the model, and allows us to calculate the AUC, which would be the area under the curve. We note in table 6 that AUC is 1 and the precision is 100%. Recall that the certainty of each rule (Ri) is determined by its degree of triggering, which varies between 0 and 1. We see that all 3 rules have a high level of triggering (greater than or equal to 0.85). The above results tell us that the model is robust and performs a perfect classification.

4.2.2 Case study 2

Objective The second case study presents a variation, where at least one animal is labeled sick, and paddock performance is good, despite the weather season. The rules that will be activated are those of 2 antecedents, since the paddock performance will be good and will not negatively affect animal fattening.

System input The input data are as follows:

Table 7: Representation of livestock data and classification of animal status in experiment 2

Age (months)	Age initial(kg)	Age end(kg)	ID animal	Prediction	Grade membership
19	332.0	334.5431	V1	0	0.2543
29	348.0	356.5431	V2	1	0.8543
23	327.0	335.5431	V3	1	0.8543
18	361.0	369.5431	V4	1	0.8543
22	344.0	352.5431	V5	1	0.8543
19	363.0	371.5431	V6	1	0.8543
22	328.0	336.5431	V7	1	0.8543
22	366.0	374.5431	V8	1	0.8543
19	359.0	367.5431	V9	1	0.8543
26	380.0	388.1348	V10	1	0.8134

Table 8 contains the data used for paddock entry. It shows the occupied paddock, the name of the forage used in the paddock, and the weather condition.

Table 8: Paddock performance in experiment 2.

Name	Climate	Pasture	Forage	Status
Humidicola comum Tuly o Quicuio da Amazönia	Seco	1	7	Bueno

The same table 8 shows the forage column, which represents paddock quality. The status column shows the paddock yield.

Analysis of results With the existing fuzzy rules, we saw that the fuzzy classifier system infers that only one animal is sick for that given input (see table 7). Once several iterations of the fuzzy system have been performed, the adaptive system of rules is invoked.

The evolution of the best individual through the generations of the GA is observed in Figure 14. The rules activated using the best individual of the 1st generation (see Figure 14.1) and the training dataset, are shown in Figure 13.1, but these rules do not satisfy the system, since it only has rules with stable consequent. In the 2nd iteration, in Figure 14.2, its activated rules with the training dataset can be seen in Figure 13.2. Already in that iteration, an improvement in the rules is noticed because the sick state appears in the consequent.

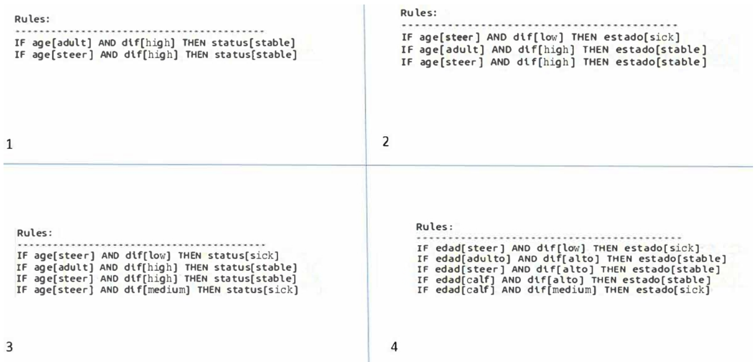

Figure 13: Evolution of the activated rules in experiment 2.

Finally, in the 4th iteration, the stop condition is reached, and its best individual represents the final solution (see Figure 14.4). In this case, the final rules (see Figure 13.4) are the ones needed for the diagnostic system for the dataset shown in table 7.

Finally, with the final fuzzy rules (see Figure 13.4), the diagnostic system is tested using the test data. With the result of the inference process, the quality metrics of the system are calculated (see table 9 and Figure 15).

Table 9: Case 2 metrics.

Metrics	Values
Accuracy	97%
Rule certainty	R1:0.85, R2:0.88,R3:0.90,R4:0.85,R5:0.85
AUC	1

We note in table 9 that AUC is 0.98, and the precision 97%. On the other hand, the certainty of each final fuzzy rule is equal or greater than 0.85. All of the above tells us that the model is robust, performs a good diagnosis, and its rules are adequate for the input data.

4.2.3 Case study 3

Objective The third case study presents a variation, which consists in analyzing the animal fattening, taking into account the paddock performance when being regular. The rules that will be activated are those of 3 antecedents, in this case, the paddock variable is activated because it has a negative effect on animal fattening.

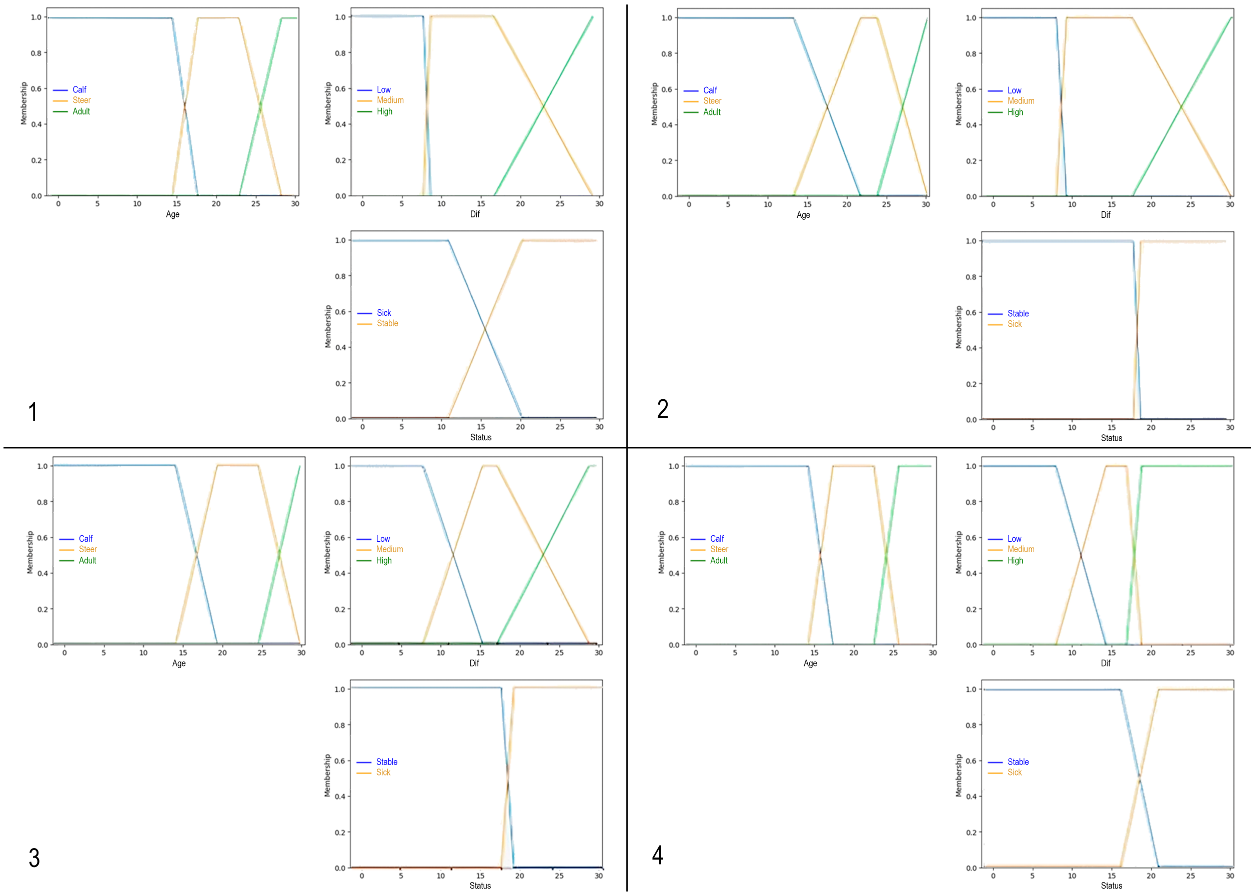

Figure 14: Adaptation of membership functions.

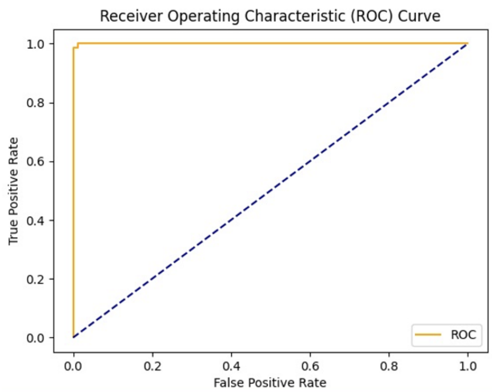

Figure 15: ROC curve of case 2.

Input data is as follows Table 10 presents a partial view of the historical cattle fattening data. Based on what was said for the previous scenarios, we note that there are several animals that are outside the ideal range (see first 4 columns). We look for the fuzzy classifier system to identify them, now also, using the paddock variable.

Table 10: Representation of livestock data and classification of Animal status in experiment 3.

Age (months)	Weight initial(kg)	Weight end(kg)	ID animal	Prediction	Grade membership
21	434.8377	438.0388	V1	0	0.5201
29	450.8377	456.0388	V2	1	0.5201

Table 10: Representation of livestock data and classification of Animal status in experiment 3.

Age (months)	Weight initial(kg)	Weight end(kg)	ID animal	Prediction	Grade membership
23	429.8377	435.0388	V3	1	0.5201
22	463.8377	469.0388	V4	1	0.5201
22	446.8377	452.0388	V5	1	0.5201
22	465.8377	471.0388	V6	1	0.5201
22	430.8377	436.0388	V7	1	0.5201
27	443.8223	448.0238	V11	0	0.4201
23	451.8223	456.0238	V12	0	0.4201
27	448.8223	453.0238	V13	0	0.4201

Using our classifier system, we see in table 10, in the column degree of membership, to the stable label in low in some cases (it determines that value). This means that they belong very little to the stable label (that is why we see in the prediction column their label with the value 0).

Table 11: Experiment 3 paddock data .

Name	Climate	Paddock
BRS Zuri	Seca	1

Table 11 contains the data used for paddock entry. It shows the occupied paddock, the name of the forage used in the paddock, and the weather condition.

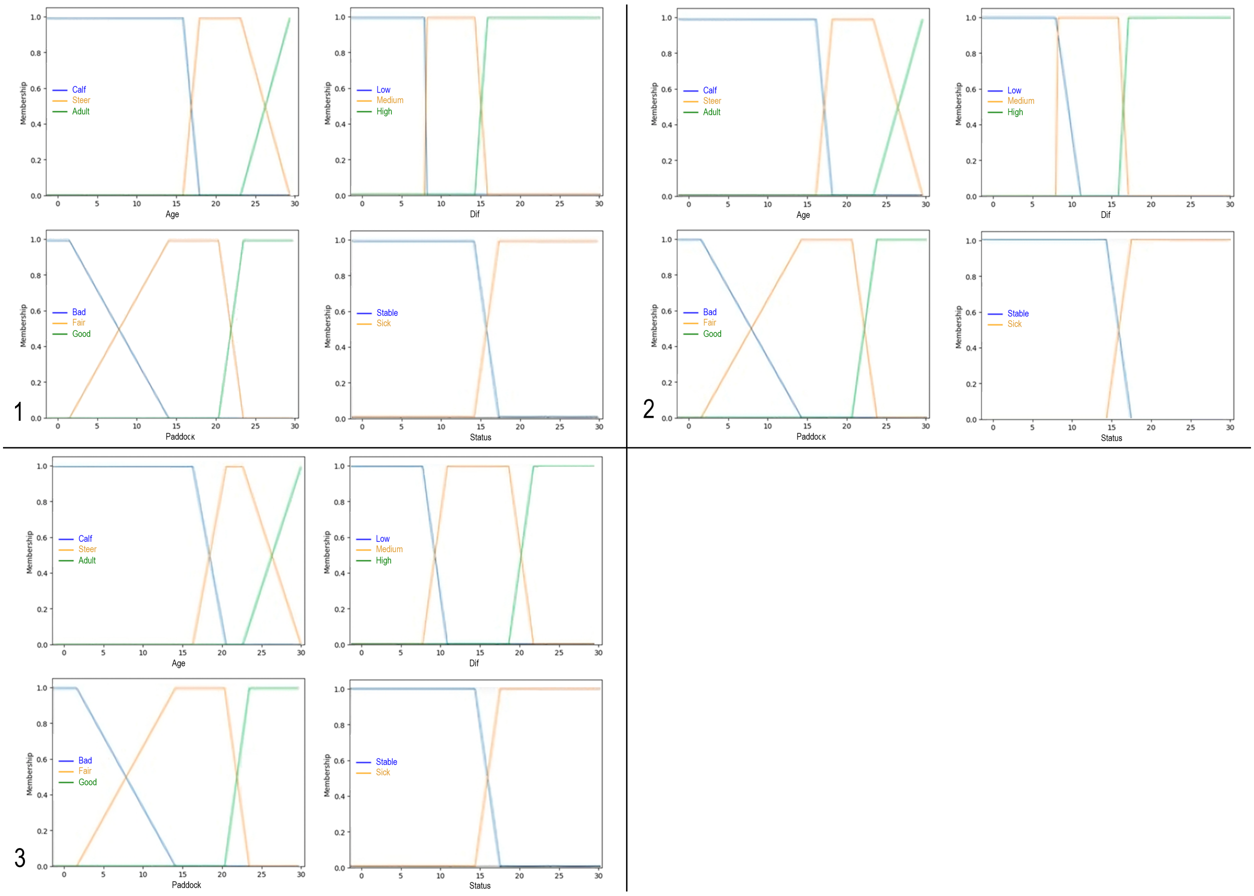

Figure 16: Adaptation of membership functions.

Figure 16 shows the 4 fuzzy variables (now with the paddock), and how their fuzzy sets are being adjusted. Figure 16.1 shows the best individual of the first iteration and the rules activated with the training dataset

1 Rules: .... IF age[high] AND dif[high] THEN status[stable] IF age[steer] AND dif[high] THEN status[stable]	2 Rules: .... IF age[steer] AND dif[low] THEN status[sick] IF age[adult] AND dif[high] THEN status[stable] IF age[steer] AND dif[high] THEN status[stable]
3 Rules: .... IF age[steer] AND dif[low] THEN status[sick] IF age[adult] AND dif[high] THEN status[stable] IF age[steer] AND dif[high] THEN status[stable] IF age[steer] AND dif[medium] THEN status[sick]	4 Rules: .... IF age[steer] AND dif[low] THEN status[sick] IF age[adult] AND dif[high] THEN status[stable] IF age[steer] AND dif[high] THEN status[stable] IF age[calf] AND dif[high] THEN status[stable] IF age[calf] AND dif[medium] THEN status[sick]

Figure 17: Evolution of the rules that are activated in case 3.

in Figure 17.2, and so on through the iterations. Figure 16.3 shows the final solution of the GA when it converges (individual with the highest value in the fitness function), and Figure 17.3 shows the rules activated with the training dataset. This will be the final fuzzy rule base. There are a larger number of rules, as more rules are needed to control the systfem.

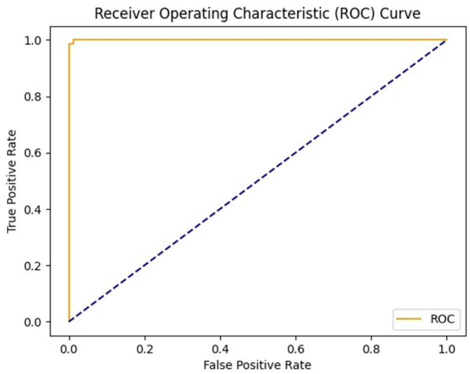

Figure 18: ROC curve in case 3.

Table 12: Metrics of case 3.

Metrics	Values
Accuracy	95%
Certainty of rules	R1:0.88, R2:0.75, R3:0.89, R4:0.85, R5:0.85, R6:0.75
AUC	1

Finally, with the final fuzzy rules, the system is tested using the test data, and the quality metrics are calculated (see Table 12 and Figure 18).

4.3 Recommendation System Test Scenario

This system is activated once situations such as case 3 are detected, where the weight loss is caused by the grass in the paddock. Case 3 indicates that it is important to take action, as the grass in the paddock is not performing. This situation has a direct impact on cattle fattening and, ultimately, on the profitability and success of the cattle business. A pasture that is not performing adequately will not provide the right amount of feed for the cattle, resulting in reduced beef production.

In particular, the recommendation system is able to recommend, with the environmental parameters and soil characteristics of the pasture, the best type of grass to use. Specifically, in case 3, paddock 1 is planted with BRS Zuri grass and the climate is dry. Immediately, a soil survey is done to establish all the input variables to the classifier model (see Table 13).

Table 13: Input to the classifier model.

Variable	Value
Nitrogen	95
Phosphorus	42
Potassium	43
Temperature	20.87974371
Humidity	82.00274423
pH	6.502985292000001
Rainfall	202.9355362
Water weight gain	600 a 640 gr/day
Dry weight gain	420 gr/day

These data are fed to the classifier model trained with random forests, and the recommendation given by our system is that the best pasture for paddock 1 should be BRS Paiaguás (see Table 14). Thus, the recommendation system indicates the best type of grass to use in that paddock to improve animal fattening.

Table 14: Recommendation for paddock 1 in case 3.

Name	Climate	Paddock
BRS Paiaguás	Seca	1

5 Comparison with other studies

To compare this work with other similar works, we proceeded to define four criteria, which are:

- *Cri*1: The work uses non-intrusive schemes for the supervision of the animal fattening process.
- *Cri*2: The work uses intelligent techniques.
- *Cri*3: The work uses machine learning to improve the monitoring process.
- *Cri*4: The work jointly analyzes grazing and animal welfare.

These criteria are relevant in precision livestock farming because they fulfill 2 important aspects, which are the use of automatic technologies of industry 4.0, and strive for animal welfare to improve livestock production. Comparison with previous work is shown below in Table 15.

Table 15: Comparison with other works.

	Cri1	Cri2	Cri3	Cri4
[5]	✗	✓	✓	✗
[6]	✗	✓	✓	✓
[7]	✗	✓	✓	✗
[8]	✓	✗	✓	✗
[9]	✓	✗	✓	✗
[14]	✗	✓	✓	✗
[11]	✗	✓	✓	✗
This work	✓	✓	✓	✓

The first criterion is met by [8] and [9], since both use computerized methods and models for the supervision process, specifically for diagnosis. The second criterion is met by [14] and [11], since they use fuzzy logic in their architecture, in one case to find malignant diseases, and in the other for the generation of a medicinal production system. In addition, [5], [6], [7] use fuzzy logic to improve farmers' decision making, whether to recommend fertilization plans for soils and grasslands, or agricultural and livestock productivity in rural settlements. The third criterion is met by all of them, since they use machine learning for different things, for example, to process acoustic information from animal chewing [8], study the environment of livestock [9], detect diseases [14], or establish the best medicinal production system [11]. Monitor fertilizer [5], production [6] and crops [7].

The fourth characteristic is only fulfilled by [6] since they study soils, grasslands and livestock productivity considering animal welfare, and our work since it is aimed at precision livestock farming in a rotational grazing environment that seeks animal welfare.

This work meets all the criteria that point to a management model of an animal fattening process, it even goes much further because, in addition to diagnosing, it recommends concrete actions. Thus, it ensures animal welfare through an adaptive fuzzy diagnostic system based on evolutionary learning (using GAs), and a recommendation system based on a classifier model to estimate the best pasture for a given paddock, all essential in precision livestock farming to ensure animal health, and make the best use of livestock in rotational grazing.

6 Conclusions

This research presented the development of a system that manages the animal fattening process in rotational paddocks. The system is composed of a fuzzy diagnostic system designed by integrating FCM, a fuzzy reasoner and GAs, in order to obtain a diagnostic model adaptive to the environment data. In addition, the management system is composed of a recommendation system based on a classifier model designed to estimate the best grass given the soil characteristics.

The proposed diagnostic system allows adapting a set of rules to diagnose the fattening process of a batch of cattle using a fuzzy inference process. This fuzzy system is characterized by its flexibility and its tolerance to inaccuracy [43], since it can perform approximate reasoning using information from the environment (the input data to the fuzzy system). On the other hand, the recommendation system uses a grass classifier model that learns from the environmental and physical-chemical variables of the soil to determine what kind of grass to use in each case.

The effectiveness of the proposed method has been demonstrated by several experimental cases, with results that are promising. The accuracy metrics have a high value, indicating that the diagnostic system manages to train quite well using the process data, with a low error rate in terms of false positives. On the other hand, certainty metrics are above 0.75, indicating that the activation levels of the updated rules are high, as they are adapted to the data (they define the usefulness of those rules). Finally, AUC is close to 1, which says that the classifier has a very low margin of error, and its level of error is almost zero. All these values confirm a high credibility in the diagnosis of the system. Likewise, the classification model has very high accuracy values (98.61%) that speak of its quality to determine the best grass for a given environmental context.

This proposal is an effective alternative to be applied in precision livestock farming, specifically in rotational grazing to diagnose cattle diseases, either by disease or by paddock performance. However, among the limitations of this work are that the system is only applicable to rotational grazing, the cattle population must be from the tropics, and only 2 climatic seasons (summer and winter) are evaluated. Thus, this system can only be used in contexts with the following characteristics: on farms that use rotational grazing, regardless of the size of the cattle herds, and that the climatic seasons are summer and winter, understanding that in the tropics, winter is a rainy season and summer is a dry season.

One of the future works is to test this management system as an autonomous cycle of data analysis tasks [44], [45] to automate the monitoring of the animal fattening process in the framework of precision livestock farming. Another future work is to extend the process of rule adaptation (which is currently only based on fitting to trapezoidal type membership functions). For example, allowing the adaptation of fuzzy sets with other membership functions (e.g., Gaussian), or even the possibility of making changes in the variables used in the rule antecedent. Along the same lines, other possible extensions are to use more context variables (e.g., explicitly the weather), to allow the number of fuzzy sets in the fuzzy variables to vary (e.g., more or fewer states to characterize the fattening process), among other improvements. Other future work on the pasture classifier model is to use real data on the soil physico-chemical variables associated with the pasture crop for each paddock.

Acknowledgements

All authors would like to thank the Vice Rector's Office for Discovery and Creation, Universidad EAFIT, for their support in this research. Likewise, the authors would like to thank the HAMADI 4.0 project, code 22-STIC-06, of the STIC-AmSud regional program, for supporting this work.

Conflicts of Interest

The authors declare there are no conflicts of interest.

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